Scale, Scope and Performance[1]

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Abstract

How scale and scope affect firm performance, and implications for the boundaries of the firm, are central questions in economics. Assessing these effects empirically, however, has proved difficult. We argue that because franchised chains are fundamentally single-product entities, we can use data on franchised chains and their parents to distinguish scale and scope effects. After controlling for chain unobserved heterogeneity via fixed effects, we find a robust evidence of positive scale effects within a chain, suggesting positive spillovers from being large. For parent company scope, i.e. firm-level product variety, which we measure by the number of other chains of the parent, we find no effect on sales per outlet, and a negative effect on the number of outlets in the chain. Finally, a change in parent company has no effect on sales per outlet, but reduces the numbers of outlets of the target chain in the following years. We conclude that increasing scale is beneficial to chains, and thus firms, but multi-chain parents seem to engage in rationalization to reduce competition among their chains/products.

1. Introduction

How does a firm's scale of operations, and the scope of its activities, affect its performance and growth? Do firms benefit from mergers, takeovers and other ownership changes, and if so why? Under what circumstances do consumers benefit from such changes as well? These questions have been central concerns in industrial organization, corporate finance, organizational economics, and in microeconomics generally, as they relate to fundamental issues such as optimal firm boundaries, productivity, and industry evolution. As a result, they have attracted much theoretical and empirical attention. However, empirical evidence concerning the importance and magnitude of scale effects on firm performance remains scarce. Moreover, studies of firm scope, its variation over time, and its effect on firm outcomes are particularly lagging behind. This is perhaps not so surprising considering that theoretical models of industry evolution have just recently begun to incorporate the notion that firms produce a variety of products and an evolving mix of products over time.[1] Thus, as noted by Bernard et al. (2006, p. 23), "Further research is needed into the respective roles of firms' intensive (how much of each product is produced*)* and extensive (how many products are produced) margins in firm growth".

In this paper, we contribute to this literature by focusing on franchised chains, where one can distinguish between scale and scope better than in any other context that has been considered to date. Specifically, we examine how scale and scope externalities (or spillovers) that may arise within- and across the chains owned by a given parent firm impact the chain's operational (rather than financial) performance. As we discuss further below, we use two measures of chain performance where one, namely sales per outlet, captures franchisee benefits to a large extent,

[1] See notably Nocke and Yeaple (2006), Klepper and Thompson, (2009) and Bernard, Redding, and Schott (2010), for evidence on, and models of, multi-product firms. See also Goldberg et al. (2009) for a comparison of patterns of product-mix changes between Indian and US firms and an assessment of how such changes relate to changes in trade policy.

while the other, namely the number of outlets, relates more directly to franchisor (i.e. parent firm) performance.[2] As a result, our setting allows us not only to better understand the role and interplay between the firm's extensive and intensive margins, and implications for overall firm behavior and performance, but also how potential benefits from scale vs. scope may be distributed across different stakeholders in a multi-product firm.[3]

As we argue further below, scale and scope are more easily defined and measured in the context of franchising than in, say, manufacturing, because franchised chains are fundamentally single-product entities.[4] This is not to say that franchised outlets sell only one product, but the set of products offered at an outlet is quite limited and intrinsically linked to the brand name. Consequently, the "menu" of products sold is chosen centrally by the franchisor and is quite stable over time. This means that we can measure scale (i.e. how much of a product is produced) using total revenues (sales) achieved in a given franchised chain. Also, though most franchised chains are owned by a parent company that owns nothing else, some parent companies own more than one chain. Some of the best-known examples of multi-chain companies include Choice Hotels International, which owns Comfort Inn, MainStay Suites, Econo Lodge and several other chains; Yum! Brands Inc., the largest fast-food restaurant company in the world, with brands such as KFC, Pizza Hut, Taco Bell, and others; and finally Service Brands International, owner of Molly Maid and Mr. Handyman. Because data on sales and number of outlets are published at the chain level, we can measure scope by the number of (other) chains owned by the parent, and

[2] As we discuss further in Section 2, per outlet sales and number of stores, and growth in these, also are typical measures used in the trade literature to compare performance across chains and their parents.

[3] This issue of who may benefit from increased scale or scope is of major concern also for manufacturing firms because of the effect this can have on divisional profits and thus manager incentives in these firms.

[4] We use the words "product" or "concept" interchangeably to mean the menu of product options offered at each outlet in a chain.

thus clearly distinguish scale from parent company scope, even when the different chains would be considered part of the same industry, as is often the case, per the examples above.[5]

Using data on the largest U.S. franchised chains and the companies that own them, we find that sales per outlet (or unit or store – we use these terms interchangeably) and the number of outlets in a chain are both positively related to chain sales from the last year in our fixed effects regressions. This suggests positive spillovers from scale, i.e. there are network advantages from being part of a larger chain. When it comes to scope, however, we find that a greater number of other chains owned by the same parent firm in the last year has no effect on sales per outlet, but has a negative effect on the number of outlets in the chain in year *t*. Our analyses of what occurs when chain ownership changes further support these findings and conclusions. Specifically, we find that ownership changes have no effect on sales per outlet in the short or long run, but they have a negative effect on the chain's number of outlets in the long run. Controlling for the timing of these events, moreover, does not affect our scale and scope results.

Since the chains owned by multi-chain firms tend to be in the same rather than different industries, we conclude that multi-chain firms find it beneficial to curb growth in their chains to reduce competition among them. In other words, our evidence is consistent with the idea that firms in the type of industries where franchising occurs engage in some form of rationalization. Our findings in that sense are consistent with those from the gasoline retail industry where outlets have been found to be located further apart when a larger fraction of them in a given market are owned by the same firm (Netz and Taylor, 2002). Finally, we find it noteworthy that effects of opposite signs for scale and scope, like those we find, would be impossible to identify,

[5] Our version of scope differs from that analyzed in Basker et al. (2008). In that paper, the authors argue that general-merchandise chains add to the scope of their stores by adding product lines when they grow in terms of outlets. Here the chains are more specialized, as noted above, and do not diversify the offerings at individual stores much at all. Instead, the firm grows in scope by diversifying into other business ideas, i.e. other chains.

and could well cancel each other out, if we had to rely on industry classifications to define scale and scope, as authors typically do when using data on manufacturing firms.

The remainder of the paper is organized as follows. In the next section, we briefly review related literature and, using a simple theoretical framework, we discuss the implications regarding how scale and scope are expected to affect our measures of performance. In Section 3, we describe our data, show descriptive statistics and discuss our empirical methodology. We present our results in Section 4 and provide concluding remarks in Section 5.

2. How Scale and Scope Can Affect Performance? – A Simple Framework

Large franchised chains are comprised of numerous geographically dispersed outlets, all of which sell a "single" menu of products under the franchisor's brand name. Knowing that customers will only travel some distance to access their products, chains tend to open more stores to reach more customers rather than grow individual stores very large.[6] Hence, as in Ferrari and Verboven (2010), we write total demand at time t as $Q_t(N_t, p_t)$, which is decreasing in price p_t and increasing in the number of outlets, N_t, but at a decreasing rate, so $Q_t''(N_t) < 0$.

Given the types of industries where franchising occurs, we expect the market for the franchisor's product to be monopolistically competitive. Thus each period, the equilibrium price p_t is determined via this competitive process within the industry and franchisees and franchisor take the price as given. In addition, franchisees pay a royalty on sales to their franchisor each period. We assume that the franchisor sets this royalty rate at a level that allows its franchisees to compete with franchisees of other chains and with independent business owners that have no

[6] Unlike in manufacturing, many services (e.g. restaurants, hotels, car repairs) cannot be shipped, so to reach a customer and facilitate 'realization' of demand, the place of production must be the same as place of consumption. Salvaneschi (1996: 76) for example describes how "McDonald's used to follow a distance rule of 3, 5 and 7 minutes of travel time. A restaurant's core part of its RTZ (retail trade zone) was under three minutes of travel time (by car), the secondary part of its RTZ was within 3 to 5 minutes, and the outer area was within 5 to 7 minutes."

such fee obligation. In other words, in a monopolistically competitive environment, the royalty rate, *r*, must be commensurate with the benefits (brand value, input cost reductions) that the franchisee derives from being part of the franchise. Moreover, we know from the literature on franchising that franchisors set a single royalty rate that applies to all franchisees joining the chain at a point in time (see Blair and Lafontaine, 2005). In addition, Lafontaine and Shaw (1999) have shown that the royalty rates are very stable over time. For this reason, we assume that *r* is basically fixed over time and the same for all franchisees in a given chain.

With similar technology and product offerings, store/outlet sizes also do not vary extensively in franchised chains. With pre-determined franchise contract terms (such as royalty rate), franchisors also have strong incentives not to grow individual franchised stores much larger than others. We therefore assume that the demand is equally distributed across outlets/franchisees and, thus, can be written as $q_t(N_t, p_t) = Q_t(N_t, p_t)/N_t$. This also captures the so-called business-stealing effect between outlets, as a result of which we assume that the demand per outlet goes down with N_t.[7]

For simplicity, and without loss of generality, we assume that all outlets in the chain are franchised, which means that they all operate under a long-term contract whereby the franchisee pays a proportion *r* of its revenues (royalty rate) each year to the franchisor.[8] Production occurs at the outlet level (as in fast-food, hotels, or cleaning services), and entails a constant cost per

[7] Franchisees in large franchised chains often express concern about business stealing, or what they refer to as encroachment. See, e.g. Kalnins (2004) and Blair and Lafontaine (2005) for more discussion.

[8] Franchise contracts last 15 years on average (Blair and Lafontaine, 2005). Also, most franchisors operate at least some of their outlets corporately. In addition, most franchise contracts also involve the payment of an upfront fixed fee - a franchise fee. This fee (or sunk cost), however, is only a small proportion of total payments by franchisees to franchisors, and is viewed in the industry mostly as compensation for the costs incurred by the franchisor in setting up a new outlet. Finally, why firms choose to franchise and why most franchisors operate some stores directly has been the subject of a sizeable literature. Typically, it is assumed that downstream operations require local effort and franchisees are better at providing this, but that franchisors also cannot extract profits so well, or incur other costs, when using franchising. See Blair and Lafontaine, 2005, especially chapter 4 for more on this. We abstract from these issues in our simple model so we can focus on those factors that are central to our empirical analyses. Allowing for company ownership and payment of upfront fees would not affect our conclusions.

unit, c, and a fixed cost, F. Due to the similarity in technology and size of the stores mentioned above, we take c and F to be the same across all outlets in a chain. Franchisee profits at time t thus can be written as:

$$\pi_t = [(1-r)p_t - c]q_t(N_t, p_t) - F. \tag{1}$$

For any chain, the franchisor's (or parent company) profit is determined by the royalty revenues collected from all the outlets, namely:

$$W_t = rp_tq_t(N_t, p_t)N_t = rp_tQ_t(N_t, p_t) \tag{2}$$

where $p_tq_t(N_t, p_t)$ are the sales revenues of each outlet, r is the royalty rate and N_t is the total number of outlets at time t. As can be seen from equation (2), for given p_t and r, franchisor profit is always increasing in the number of outlets. In other words, with r fixed, franchisors adjust to changes in market circumstances by adjusting N. Failure to do so, moreover, can lead to franchisees earning above (or below) zero profits.

Given this framework, the profitability of the franchisor (firm) and the franchisee are directly linked via the sales/revenues per outlet and the total number of outlets in a chain, which are the two measures of performance that we focus on in our analyses. Note that these measures are also the ones that the trade press and industry members rely on when assessing chain and parent firm performance.[9] In fact, given the profit functions of the franchisee and the franchisor, one can think about a store/outlet as a unit of output, and about the number of stores of the chain, N_t, as a proxy for quantity of output for the franchisor.

Since franchisor profit, per equation 2, is always increasing in N_t, the optimal number of outlets for the franchisor is implicitly determined by the franchisee zero-profit condition, which in turn also determines the equilibrium sales per outlet p_tq_t*. Thus in equilibrium our two

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[9] In studies of manufacturing authors have at times relied on gross profit margins as their measure of performance. In retail and service industries however these measures of performance have been criticized (see e.g. Manser 2005).

variables of interest - sales per outlet $(p_t Q_t(N_t^*, p_t)/N_t^*)$ and total number of outlets (N_t^*) – will be functions of the royalty rate r, franchisee costs and industry price p_t. From the profit functions it is also easy to see that factors leading to changes in sales per outlet (or local productivity) affect franchisees (i.e. the local operators) profit directly, whereas changes in the chain's number of outlets affect franchisor (or parent firm) profit most.

Changes in the scale of a chain (i.e. its total sales) and in the scope of its parent company (i.e. how many different products/chains the company owns) can affect our performance outcomes through either cost or demand. Besides these two channels, some literature also points to market power effects for scope. The formal models demonstrating externalities from scale or scope are well established in the literature, and the underlying intuition can be extended easily to franchised chains.[10] Hence, in what follows we rely on our simple framework above to demonstrate the partial equilibrium effects for the scale effects, and then only briefly discuss potential sources of scope effects. Our goal throughout is to convey intuition for what one expects to find in the data depending on the channel through which the scale and scope effects operate, and thus for our interpretation of the observed data patterns.

2.1 Scale Effects

2.1.2. Demand-side Effects

Brands play a major role in the types of markets where franchising occurs. On the demand side, then, increased scale might mean that more consumers are exposed to a brand, leading to further increases in total demand $Q_t(\cdot)$. Specifically, larger prior sales of a chain can serve as a form of advertising (or increased reputation) that helps expand future demand for the

[10] See e.g. the seminal work by J. Panzar and R. Willig (1977, 1981).

chain's product.[11] To capture such demand shift in our framework, we augment the franchisee and franchisor's profit functions as follows:

$$\pi_t = [(1\text{-}r)p_t - c]\frac{Q_t}{N_t}(N_t, p_t, S_{t\text{-}1}) - F \qquad \text{and} \qquad W_t = rp_t\, Q_t(N_t, p_t, S_{t\text{-}1})$$

where S_{t-1} represents chain scale, which we measure by total sales of the chain in the prior year, and where we assume $Q'(\cdot) > 0$ and $Q''(\cdot) < 0$ in S_{t-1}. Everything else the same, if the franchisor had set $N_{t-1} = N^*_{t-1}$ such that the franchisee zero-profit condition was binding at $t\text{-}1$, and assuming for now that $N_t = N^*_{t-1}$, the franchisees will earn higher revenues and positive profits at time t. So the shift in total demand due to greater chain sales in the previous period will generate higher sales per outlet if the franchisor, for some reason (e.g. it may take more than 1 period/year to open an outlet), cannot reap the extra profits via increasing N_t, or will result in the franchisor increasing the number of outlets if it indeed maximizes its profits, or perhaps both if there is only a partial increase towards the new N_t^* (the number of outlets that equalizes the franchisee zero-profit condition at time t).

2.2.1. Cost-based Effects

Larger scale also may allow the franchisor to negotiate better prices for inputs – and thus reduce either variable or fixed costs for its franchisees. While the franchisor profit remains as in equation (2) in this case, franchisee profit would be given by:

$$\pi_t = [(1\text{-}r)p_t - c(S_{t\text{-}1})]\frac{Q_t}{N_t}(N_t, p_t) - F(S_{t\text{-}1})$$

[11] In addition, increased scale at time $t\text{-}1$ can increase demand for the focal chain at time t by discouraging the entry or expansion of competitors at time t in spatially differentiated markets (see e.g. Schmalensee, 1978 and Eaton and Lipsey, 1979). However, as Judd (1985) points out, there must be some sunk cost of entry for entry deterrence to work. Hadfield (1991) argues that franchising can be used to make preemption credible.

where c and F stand for variable and fixed costs, both reduced now by increased S_{t-1}. All else equal, franchisees would now earn positive profits given same sales level and lower costs. The franchisor, however, again would have an incentive to capture these higher profits by increasing N_t. Since local demand $q_t = Q_t(N_t, p_t)/N_t$ is decreasing in N_t, the higher number of outlets would translate into lower sales per outlet due to the business stealing (encroachment) effect. The new lower sales per outlet, in equilibrium, would allow the franchisee to earn only zero profit again.

Regardless whether scale effects operate via demand or cost, for the purposes of our empirical analyses below, the important fact is that in equilibrium our two performance outcomes of interest – sales per outlet and total number of outlets (let's denote them Y) – can be expressed as a function of exogenous (and pre-determined) variables at time t: $Y_{it} = Y(c_i, F_i, r_i, p_t, Scale_{it-1})$, where i and t index chain and time, respectively. As we discussed above, given that both the royalty rate and franchisee costs are similar across all the outlets in a chain (ultimately determining chain heterogeneity), in our empirical analysis we control for these (to us unobserved) variables via chain fixed-effects. To control for prices, which are determined each period by the competitive process in the industry, we use the vector of industry-time trends and time dummies. We discuss our empirical methodology in detail in Section 3.2.

In the remainder of this section, we discuss various channels through which firm scope – as opposed to scale –can affect our performance measures. In our simple framework, the mechanisms behind scope can be incorporated as additional shifts in demand or costs, given chain scale. However, to fully derive these arguments we also would have to extend our framework to allow each firm to oversee multiple products and model the interactions among them. Since the conclusions follow straightforwardly, for space reasons we instead simply provide the intuition behind the arguments.

2.2 Scope Effects

2.2.1. Demand-side Effects

There are several scenarios under which increasing scope can lead to positive demand spillovers for a single chain. Hotel companies provide one example. Many hospitality firms own several chains of differing quality levels, and offer loyalty programs that cut across their chains.[12] With such programs, larger scope is likely to affect demand for all the products – i.e. chains – in the parent company's portfolio. Alternatively, parent companies may find it worthwhile to co-locate branded offerings or offer "bundles" to consumers. While such co-location can yield cost advantages, as discussed further below, it can also affect demand for the chains' products. A typical example arises in the context of the fast-food industry, where family members can have different preferences over dining out options. A location that offers products from several different fast-food brands to this group of customers has an advantage over the single-concept outlet.[13] Finally, the different chains of a parent company may benefit from each other's reputations if the parent advertises its multiple products to the same pool of customers via large-scale campaigns.[14]

Whether due to loyalty programs, bundled product offerings or potential reputation spillovers, increasing parent scope would lead to higher demand locally, and thus higher sales and greater profits for franchisees. Again, the franchisor can capture these by increasing the number of outlets in the chain, in which case the increased demand due to scope would only show up empirically in the form of increased number of chain outlets.

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[12] For an example of how such loyalty programs work, see Deighton and Shoemaker, Hilton HHonors Worldwide: Loyalty Wars, HBS case #501010.

[13] Studies of agglomeration economies in the hotel industry similarly emphasize positive spillovers in terms of heightened demand and hotel-level performance arising among co-located hotels that belong to different hotel segments (e.g. Canina et al., 2005; Chung and Kalnins, 2004).

[14] As in the case of scale, increased scope at time *t-1* also may discourage entry by competitors, leading to further increases in demand for the focal chain's product in the future.

2.2.2. Cost-based Effects

Owning several brands or chains may allow a parent company to utilize the same supplier network or share the cost of various managerial activities across different chains/products. Important cost savings – especially when it comes to activities such as franchisee training, monitoring, and other support from the parent company – can arise from efficiencies in management and related headquarters activities.[15] Combining brands in the same physical facility as in co-branding stores also can lead to lower fixed costs locally. Hence costs of operations at the outlet level – including how much the outlet must compensate its franchisor for managerial headquarter services – may be reduced as a result of increased scope of the parent company. As in the case of cost reductions due to scale effects, scope-induced cost reductions should increase the number of chain outlets, but reduce per-outlet sales within a chain.

2.2.3. Market-Power Effects

When it comes to scope, the differentiated products literature suggests another channel through which chain performance may be enhanced. We illustrate this effect with a simple example. Consider a firm that switches from selling a single product to selling two competing (i.e. substitutable) products. Such a firm would have an incentive to set higher prices for its two products compared to those that would be chosen by two separate firms, each selling just one product. In other words, maximizing: $\Pi = p_1q_1 + p_2q_2 - c_1(q_1) - c_2(q_2)$, where : $q_1 = a - b_1p_1 + b_2p_2$ and $q_2 = \alpha - \beta_2p_2 + \beta_1p_1$, yield higher prices (and lower quantities) than the prices (and quantities) that maximize $\Pi_1 = p_1q_1 - c_1(q_1)$ and $\Pi_2 = p_2q_2 - c_2(q_2)$ under the same demand conditions. Fundamentally, the joint owner now internalizes the lost sales of its other product that result from pricing either product aggressively, so it maximizes profits by being less

[15] See Cohen, D. (2010) for a discussion of such efficiencies at Focus Brands Inc.

aggressive and selling less of both products at higher prices.[16] Consistent with Gandhi et al. (2008) and the literature on gasoline retailing (e.g. Netz and Taylor, 2002), since the number of outlets in a chain can be interpreted as a measure of output, as mentioned earlier, the implication for our variables of interest is that the number of outlets should be lower for chains owned by multi-chain firms. Moreover, this effect is expected to be greater the greater the parent company scope as long as the various products sold by the parent company are substitutable. The effect of parent company scope on per-outlet sales is ambiguous, however, as reduced competition/encroachment between the stores of the same chain should lead to greater sales per outlet, but the movement up along the outlet demand curve, due to higher prices, where presumably the starting point is in the elastic portion of the demand curve, would have the opposite effect.[17]

3. Data and Methodology

3.1 Data

The data in this paper are obtained from the *Top 200 Franchise Systems*, published annually by the *Franchise Times* magazine, since 1999. This annual ranking of the largest U.S. franchised chains – as measured by their worldwide sales in the previous year – gives data for up to 300 largest chains depending on the year of publication. Specifically, given that each listing gives data for the previous year, we have data for the largest 225 franchised chains in 1998 and

[16] Thomadsen (2005) finds supporting evidence. Specifically, using data on all fast-food outlets of McDonald's and Burger King in Santa Clara county in California, he shows in his counterfactual experiments that increases in local market power, which occur as existing franchisees purchase existing company owned or other franchisee owned outlets, can have a large positive effect on prices at the merging, and other outlets in the same chain.

[17] There is a related literature on the effects of mergers on product variety. See notably Richard (1993), Berry and Waldfogel (2001), Watson (2008), or Draganska, Mazzeo and Seim (2009). However, most of these studies focus on the effects of mergers on the acquiring firm's product mix (i.e. number of products offered) not on changes in the quantities supplied/offered by the acquired chain, or single product entities, as we do.

2000, largest 200 in 1999, largest 250 chains in 2001 and 2002, and largest 300 chains each year from 2003 to 2007.

Unfortunately, the U.S. government does not collect data on franchising. As a result, the population of franchisors operating in the U.S. and the amount of activity they engage in each year are not so straightforward to assess. However, in a study commissioned by the trade group - International Franchise Association, PricewaterhouseCoopers (2008, p. 7) reported that business-format franchisors operated 773,436 outlets in the U.S. in 2005.[18] The 300 chains in our data which account for about 15% of the total number of business-format franchisors in the U.S. according to Bond (2007), operate 308,600 outlets domestically according to our sources. Given the population estimate above, these chains thus amount to about 40% of total franchised outlets in the U.S. Moreover, despite being comprised of only largest chains, the size range of the chains is quite wide (see Table 1 and discussion below). Finally, issues of scale and scope are most relevant for larger chains and firms. Hence, we believe that the chains in our data are the most relevant ones to consider when it comes to the questions we focus on.

The information provided for each chain each year includes not only the chain's worldwide sales, but also its total number of outlets (including franchised and company-managed outlets), the percentage of franchised outlets and the name of its parent company. The latter allows us to identify ownership changes as well as obtain a measure of the parent's other operations which we measure using the number of other chains in our listings that are owned by the same parent company. Though some parent companies also may own small chains that are

[18] All the chains in our data are business-format franchises, where the franchisor (parent firm) sells the right to use its brand name (or to use one of its brand names) and information about how to start and run the business to the franchisees in exchange, mostly, for sales-based royalty payments. The other type of franchising, often called traditional franchising, is comprised of car dealerships, gasoline retailing and soft-drink bottling. See Blair and Lafontaine (2005) for more details.

not included in the listings, a measure based on their ownership of larger chains captures most of their economic activity and, thus, better reflects what we believe is “relevant” scope.[19]

Our unbalanced panel data set contains information concerning 502 different chains over a maximum period of 10 years, for a total of 2648 observations. However, since we use lagged explanatory variables in all our analyses, and some chains have missing sales or total units in some years, our final sample effectively starts in 1999 and contains 1970 or 1972 observations depending on the dependent variable, across 374 chains, i.e. about 5.3 observations per chain on average. We classify the chains among 20 industry groups, as described in the appendix.

Table 1 shows descriptive statistics for our final sample for all the variables we use in our empirical analyses (we explain variable measurement in more detail in the methodology section). It also shows that the chains in this sample are major multinational brands, with annual worldwide sales of more than 1.46 billion dollars on average over the period of our data, and an average of 1655 outlets per chain. The average yearly sales per outlet are above 1.5 million dollars, but this varies importantly across chains from just $20,000 (for some cleaning services franchises) to $29 million (for some hotel chains). This cross-chain variation underscores the importance of controlling for unobserved chain heterogeneity in our analyses below.

Because the descriptive statistics above are averages calculated over almost a decade, in Figure 1 we show the sales per outlet, the number of outlets per chain, and the number of parent’s other chains on average every year from 1999 to 2007. [20] This figure suggests that despite the differences among the chains, and unbalanced nature of our data, the annual averages

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[19] Moreover, trying to add small chains, for which the reported data are often noisier or not reported as systematically, could lead to measurement errors and potentially bias our analyses.
[20] To facilitate comparisons, in Figures 1-3 we deflate the sales per outlet to adjusted 1999 dollars using the consumer price index for all urban consumers (CPI-U) published by the Bureau of Labor Statistics (ftp://ftp.bls.gov/pub/special.requests/cpi/cpiai.txt).

of sales per outlet and of number of outlets are quite comparable across years in our data. Thus there is no indication of any large-scale structural break or other sampling issue that could bias our analyses. The average number of other chains of the same parent varies to a greater extent over time, however. Because of changes in the listing's coverage, one may worry that some of this may be due to measurement error for this variable. However, comparing this measure to its more conservative alternative, also shown in Figure 1, where scope is measured using only data on the largest 200 chains each year (rather than all chains available in a given year) clearly shows that the evolution of the two measures is very similar. Thus we conclude that the variance in parents' other operations over time reflects real factors, e.g. changes in ownership, rather than changes in data coverage.

We explore the issue of ownership changes in more depth in Figure 2, by showing the number of chains that experienced a parent change each year, along with their mean sales per outlet and total outlets in that year. The figure does not show any relationship between ownership changes and sales per outlets. Specifically, while the number of parent changes varies across years, average sales per outlet remain quite stable over time. As for ownership changes and the average number of outlets in the chain, we see some indication that when more parent changes occur, chains tend to have fewer outlets on average, at least for some pairs of years, but the reverse is true in other cases. Thus aggregate data patterns are not very informative, suggesting one needs to control for other factors - as we do in our analyses below - to uncover the relationships of interest.

In Figures 3 and 4, we show the kernel-density estimates of the distribution of the (log of) sales per outlet and number of outlets, respectively, for the top 200 chains in 1999 and then again in 2007. These figures illustrate the rich variation in these variables across chains, as well as interesting dynamics over time. Specifically, while annual averages for both per outlet sales and chain's total outlets are relatively stable over time, per Figure 1, we see in Figure 3 that the distribution of the (log of) sales per outlet is shifting to the right over time, and the skewness of the distribution goes down from 0.39 (in 1999) to 0.00 (2007). Thus sales per outlet are increasing over time among several chains, leading to a more symmetric distribution and convergence of mean and median. This occurs despite the fact that the distribution of the number of outlets does not change much (skewness: 0.69 vs. 0.72) between the same two years.

In Table 2, we focus on the phenomenon of multi-chain ownership by parent companies by showing the number of chains owned by the parents in the first year of our data, in 1998, and then again in 2007. This table shows that most chains belong to parents that own no other chain, and that the distribution of chain ownership among parents has not changed much over the period of our data. Since the sample contains more chains in later years, 87 chains in our data in 1998 were owned by a parent that owned some other top chain, compared to 101 chains in 2007. Still, in terms of percentages, these are quite similar - 39 vs. 34% of the chains, respectively. Note that from the descriptive statistics for the "Parent Change Yr Dummy Variable" in Table 1, ownership changes occurred in 3.7% of the observations in our data, for a total of 74 chains in our sample.[21] Thus large franchise chains do not change hands very frequently. Finally, though this is not shown in the table, we find that most multi-chain firms tend to own chains in the same industry. Using the list of franchise industry groups in the Appendix, we find that parent companies that own more than one chain in our data operate in only 1.3 different industries on average. Alternatively, focusing on parents with exactly two chains, we find that both chains are in the same industry in 78% of the cases.

[21] There are two chains for which we could not reliably determine the year of ownership change and thus identify the year when the parent change dummy variable should equal one. Thus, we have some missing values in our parent change dummy variable.

While the above are simple aggregate statistics, they point towards interesting dynamics among and within the chains. To explore whether these are driven at least in part by spillovers from scale or scope, and, when it comes to scope, whether ownership changes matter separately from organic changes in the scope of a parent company's other activities, we now turn to regression analyses.

3.2 Empirical Methodology

Given our discussion in Section 2, our empirical goal is to assess whether there are spillovers (i.e. positive/negative returns) from scale within a chain, and/or spillovers from scope among the chains of the same parent, and to evaluate their potential magnitudes. In addition, we examine whether changes in parent ownership affect spillover effects from scope.

To explore these questions, we estimate an augmented form of our performance equation as follows:

$$Y_{it} = f(Scale_{it-1}, Scope_{it-1}, \boldsymbol{X_{it}}, Parent\ Change_{it}, Parent\ Change_{it} * Scope_{it-1}) exp(\varepsilon_{it}) \quad (3)$$

where i and t again index chain and year respectively. In this equation, Y_{it} stands for sales per outlet, which we view as a measure of local productivity (potential franchisee benefit), and total outlets, which we view as a measure of total chain performance (franchisor benefit).

As mentioned above, we measure *Scale* using the total sales of the chain/product. *Scope* is meant to represent the impact of other chains/products that belong to the same parent, which we measure using the number of other chains of the same parent.[22] Since we do not expect spillovers to be realized immediately, per our discussion in Section 2, we measure both scale and

[22] Though it might be interesting to further split the scope measure among products/chains within- and across- our 20 industries, given that ,as mentioned above, most of the multi-product firms in this setting operate within the same industry, it is difficult to reliably identify such disaggregated scope effects while also controlling for chain (and thus industry) fixed effects.

scope at time *t-1*. In other words, if the sales of the chain increased in the previous year for some reason, this is more likely to impact the local productivity or total number of outlets in the chain the next rather than the same year.

Using lags, and treating our main explanatory variables as predetermined at time *t* when we measure chain performance, also helps alleviate potential reverse causality issues that may arise in this type of analyses.[23] To further address potential endogeneity issues that could arise if our measures of performance and variables of interest were driven by common but (to us) unobserved shocks, $\boldsymbol{X_{it}}$ includes a vector of year dummy variables and a vector of cross-effects between industry dummy variables and a time trend. Moreover, when using per outlet sales as our dependent variable, the impact of any unobserved shock affecting total chain sales and the number of outlets is eliminated, to a large extent, by taking the ratio of the two. In our estimations, year dummy variables control for various unobserved macro-level shocks, including inflation, changes in aggregate demand or supply due to business cycles (e.g. recession or "dot.com" bubble), as well as potential political or regulatory changes in particular years. In addition, the vector of industry-time trend cross-effects control for potential differences in the growth rates of the industries in which the chains operate. Such differences in growth could arise in our setting due to changes in competition and industry prices, regulation, technological trends (leading to cost changes) or changes in people's preferences for particular products. Thus, within each industry, separate time-trends help us capture the unobserved, and potentially correlated shocks, that might be affecting performance and variables of interest. The fact that these industry time trends are jointly significant in all our specifications confirms the importance of controlling for them in our analyses.

[23] Different timing also helps to eliminate any accounting relationship that would be present between sales per outlet and total chain sales if we measured both at time *t*.

Measuring performance, as well as scale and scope, on a worldwide basis – as opposed to focusing on a particular region/market such as the U.S. – further helps alleviate some potential endogeneity concerns. Specifically, firms with global activities are diversified geographically, so they are not so subject to market-specific shocks/risks. As a result their worldwide performance should be more stable, and driven mostly by the type of industry and macro-level shocks that we already control for with time fixed effects and industry time trends. Finally, controlling for chain fixed effects (see below) further helps to address problems associated with endogeneity and self-selection.

To examine the impact of ownership changes on chain performance, and their potential impact on spillovers from scope, in equation (3) we also include a *Parent Change* dummy variable, and its cross effect with our measure of scope.[24] Moreover, to distinguish between the short-run and long-run impact of the change in parent, we use one of two versions of the *Parent Change* dummy variable. First, we explore the short-run effect using a dummy variable set equal to 1 in the year that the chain's ownership changes, and 0 otherwise. We refer to this variable as the "Parent Change Yr Dummy variable." However, since ownership changes may take some time to affect operational performance, we expect parent changes to potentially have an observable effect on the chain's performance over a longer time period. To analyze the long run impact, we define a dummy variable set equal to 1 from the year of parent change onwards, and 0 in all years before. We refer to this variable as the "From Parent Change Yr Dummy Variable." In other words, this dummy variable compares the chain's performance after the ownership change to its performance in the years before the ownership change.

[24] Very few chains experience multiple ownership changes during our sample period. Thus we consider only the impact of the first parent change observed in our data. In Section 4.3 we verify that chains with multiple ownership changes are not driving our results. Also, since parent changes affect only the size of parents, we consider only cross-effects of our Parent Change dummy with scope.

Since these variables comprise a mix of continuous, discrete and binary variables, and to allow for non-linear relationships, we estimate the above equation in semi-log form. Specifically, we include both performance and scale measures in logarithmic form, and estimate the impact of scale on performance in the form of an elasticity.[25] As a result, whether the scale coefficient is smaller (larger) than one allows us to determine whether there are decreasing (increasing) returns to scale within a chain. We include the dummy variables described above, and scope, i.e. the number of other chains, linearly in the regressions, however. As already noted (see Table 2) about 60% the chains in our data belong to parents with no other chain, so their scope equals zero. Moreover, the range of positive values is quite limited (the mean is 1.37 chains, see Table 1) so adding just one more product/chain by a company represents a substantial change.[26] Hence, we assess the impact of scope in the form of a semi-elasticity, i.e. the percentage increase in performance due to a one chain increase in scope. Including scope in levels as opposed to logs is also consistent with the notion that scope effects shift the performance equation (see eq. (4) below) and thus when scope is equal to zero, the chain may still exhibit non-zero performance effects driven by its scale.

We assume that $\varepsilon_{it} = \mu_i + u_{it}$ is a composite error term, where μ_i represents chain-level unobserved heterogeneity correlated with our regressors. We therefore estimate all specifications

[25] Though the chain's number of outlets is a count variable, we treat it as continuous in our analyses for several reasons. First, we do not have any observation where this variable is 0 as would be typical for count models. Second, as Figure 4 shows, the distribution of the (log of) this variable is fairly close to a normal distribution. Third, as shown in Table 1, the dispersion of values is quite large, ranging from 29 to more than 33818 units (with a mean of 1655 outlets). Not surprisingly then, when we estimated Poisson fixed effects models, which would be more suitable for a count dependent variable, the Poisson distribution was rejected in our data. On the other hand, taking logs in general helps to smooth out impact of such dispersed values.

[26] Due to that also, an often used approach of adding 1 to zero values would be conceptually very misleading and could bias our analysis.

using chain-level fixed effects.[27] Controlling for chain fixed effects is very important in our context, given the cross-chain differences we found in Section 3.1. In particular, this helps us address potential endogeneity issues due to self-selection. Also, ownership changes may be correlated with performance if new parents target more or less efficient chains. Second, chain fixed effects help us control for unobserved (to us) characteristics at the chain, industry or market level that do not change much during the time we observe the chain in our sample (which averages 5.3 years). This includes franchise contract terms such as the royalty rate (see Section 2), chain efficiency or how successful the product concept is, as well as other characteristics such as being owned all along by a parent company that is better or worse at providing corporate support, or having more/less mobile customers,[28] or operating overall in a more profitable industry or markets, or specifics of a chain's ownership structure, such as how much the chain is franchised.[29] All these unobserved characteristics may be correlated with scale and/or scope, and also affect performance, which would bias our results if we did not control for them via chain fixed effects.

Finally, since the variation in chain performance may differ across chains, and observations might be correlated within chains due to unobserved and *uncorrelated* heterogeneity (i.e. heterogeneity that is uncorrelated with our regressors, in addition to

[27] When we estimated random effect specifications, the estimated coefficients were notably different. The assumption of correlated unobserved heterogeneity was also confirmed by Hausman tests, which rejected the random effects models.

[28] Brickley (1999) notes that externalities among outlets are expected to be more important in industries/products with more mobile/non-repeat customers (i.e. customers with lower switching costs) such as fast food than in industries with less mobile customers, e.g. health-care.

[29] Lafontaine and Shaw (2005) show that mature chains – as in our data – keep relatively stable mixes of company-owned and franchised outlets. We also find that the percentage of franchised outlets is quite stable for the chains in our data.

correlated heterogeneity captured by chain fixed effects), we adjust standard errors for heteroscedascity and chain-level clusters in all estimations.[30]

Our empirical specification can be expressed *in levels* as follows:

$$Y_{it} = A_i *(Scale_{it-1})^{\beta} \exp\{\alpha Scope_{it-1} + \gamma Parent\ Change_{it} + \theta Parent\ Change_{it} * Scope_{it-1} + \boldsymbol{\Omega' X}_{it-1} + u_{it}\} \quad (4)$$

where: $A_i = e^{\mu_i}$ represents the component of chain performance that is associated with chain unobserved efficiency, and any spillovers from scope, parent changes, aggregate/industry and other shocks serve as performance shifters for any given scale effect. Hence, keeping all these other factors constant between t and $t-1$, chain performance at time t would simply be driven by chain unobserved efficiency and its scale from time $t-1$, i.e. $Y_{it} = A_i *(Scale_{it-1})^{\beta}$. So, if the impact of chain scale on sales per outlet was found to be β=0.1*,* the implication would be that if the chain's worldwide sales were 20% higher the last year, the outlet-level sales this year would be about 2% higher on average solely due to the increased reputation or other scale spillover effects discussed in Section 2.

4. Results and Interpretation

4.1 Baseline Specification

Our main results are summarized in Tables 3 and 4, where Table 3 focuses on sales per outlet, while Table 4 is about the number of outlets in the chain. To better assess whether our estimates of scale/scope spillovers are sensitive to parent ownership changes, in both tables we first present results that do no incorporate any parent change dummy variables. In this case, we simply measure the chains scale and its parent's scope based on who owns the chain at any given point in time, ignoring the fact that differences in scope may be due to either ownership changes

[30] See Stock and Watson (2008) for more discussion about the consistency and efficiency of different estimators for standard errors in panel data fixed-effects regressions.

or organic growth in firm product variety. We then show results when we introduce the year of parent change dummy variable, and its interaction with our measure of parent company scope. We interpret the results from this specification as identifying the short-term effects of ownership changes. Finally, in column 3 of both tables, we include instead the parent change dummy variable that is set equal to one for the year of, and all years after, the chain becomes owned by a different parent. We interpret the results from this specification as showing the long-run effects of ownership changes.

Results across all columns in Tables 3 and 4 show evidence of positive scale effects for the chains in our data. The estimated elasticities suggest that sales per outlet increase on average by 0.15% (cca. $2310 given a mean of $1.54M), and the total number of outlets increases by 0.37% (cca. 6 outlets) in the current year if the chain's total sales went up by 1% in the previous year. As described in Section 2, such scale spillovers would be consistent with the positive demand (or reputation) effects, rather than cost-reducing effects. Given that the estimated elasticities are below one, our results also imply that returns to scale are decreasing. Hence, in the long run, everything else the same, chains should converge in size to chain-specific sizes.[31]

As for scope, the results are again very consistent across our specifications. However, in this case, we find no significant scope effect on sales per outlet (or local productivity), and statistically significant, but negative, rather than positive, scope effects for total units in the chain. The latter, moreover, remains the same whether or not we control for changes in parent company. Specifically, we find that if the parent company added one chain/product to its product mix last year, the number of outlets of the focal chain is lower by about 1%, or 16 outlets on average, this year. Thus when the parent company is increasingly involved in other activities, as captured by the number of its other chains in the previous year, it tends to downsize the focal

[31] See Kosová and Lafontaine (2010) for more on size-convergence among franchised chains.

chain this year. This reduction is consistent with the idea that the parent company rationalizes its operations, and thus reduces competition among the chains it owns. An alternative, and perhaps complementary, explanation might be that the parent company has limited resources – managerial or financial – and when expanding into *other* chains/products, it does not have the resources to also grow the focal chain as extensively as it would have without these other chains. In this way, our results support both the market power argument, and the implications of the recent models on dynamics of multi-product firms that imply that there are limits to firm scope (e.g. Bernard et al., 2010; Nocke and Yeaple, 2006; or Mitchell, 2000). However, the latter explanation would be more likely to yield *a lack of growth* for the focal chain, not a reduction in the existing number of outlets. In that sense, our negative scope results are more consistent with the parent company trying to reduce competition among its product offerings.

Finally, in Table 3 we see that there are neither short- nor long-term effects of ownership changes on sales per outlet, nor any significant differences in how scope interacts with sales per outlet as a result of parent changes. When it comes to the total number of outlets in the chain, we also find a significant negative effect of parent changes that is stronger in the long than the short run. We find no change in the strength of the scope spillover effects, however, associated with a parent change. Specifically, the coefficients of the interaction terms between scope and the short and long-term parent change dummy variables are insignificant. Consequently, a change in parent company is associated with a reduction in the number of outlets by up to 7%, or about 118 (at the mean of 1655) outlets, on average for chains in the years following such a change (on average about three years in our sample), but it does not affect how the breadth of activities of the parent relates to chain size. Put differently, given that we control for chain fixed effects and thus identification comes from the chains that experienced a change in parent company during our sample period (i.e. our control group are chain years without parent changes), our long-term parent dummy results imply that chains have about 118 outlets less on average in those years that follow a parent change.

These results imply that ownership changes reduce the number of outlets in the target chains directly. One interpretation might be that new parents try to get rid of low performing stores. However the lack of significant effect of ownership changes on sales per outlet, especially in the long run, contradicts this interpretation. In particular, if the new parent were shedding poorly performing outlets, average sales per outlet or local store productivity should increase in the years following the ownership change as pruning of low-sales outlets occurs. In other words, we should see a positive impact of the "From Parent Change Yr Dummy" on average sales per outlet as only the higher-sales stores remain in operation.

One might argue instead that new owners reduce the number of outlets not by getting rid of low-sales outlets, but rather of those that operate at high cost. In this case, sales per outlet need not change as a result of pruning. But as mentioned earlier, the fees that franchisees pay to their parent company are based on outlet sales, not profits. Thus, the parent company has no incentive to get rid of stores whose sales are high but profits are low due to high costs and inefficient franchisees. Instead, as anecdotal evidence and our discussions with industry practitioners imply, they would simply replace the franchisee. We conclude that there is no evidence, in our setting, to support the idea that the reduction in number of outlets that results from a change in parent is due to pruning of low-performance outlets.

In summary, we have shown evidence of scale and scope spillovers both within and across chains. However, while the within-chain scale effects are positive for both our performance measures, the cross-chain scope effect is negative, contrary to what one would expect based on traditional arguments in the literature that emphasize cost reductions or demand-enhancing effects across different products/activities of a multi-product company. More precisely, since average sales per outlet are unaffected by parent scope, while the number of outlets goes down, we can only conclude that chain total sales go down, overall, with increases in parent company scope.[32] The parent company presumably benefits from reduced competition among its brands, and the resulting higher product prices as discussed in Section 2.2.3. In that sense, once again, our results point to market-power motivations by a diversified parent company as the most plausible explanation for the scope effects we find. The fact that parent company changes further reduce the number of outlets of the focal chain, without otherwise affecting the negative scope effects we find in our data, only reinforces this conclusion. From a policy perspective our results suggest that parent firms that increase their product scope by acquiring chains go on to reduce the number of outlets of both their newly acquired as well as their previously-owned chains.

4.2 Robustness

We conducted several analyses to verify the robustness of our results. The results are reported in Tables 5 and 6, where Table 5 again focuses on sales per outlet while Table 6 shows corresponding regressions for the total number of outlets in the chain.

The first two columns of both tables correspond to columns 2 and 3 of Tables 3 and 4. There we restrict our sample to just those chains with 3 or more consecutive years of data. We do so for two reasons.

First, as discussed above, in all our estimations we control for unobserved chain/product-level heterogeneity by including chain fixed effects (e.g. successful/unsuccessful chain or

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[32] This conclusion is also consistent with our simple framework in Section 2, where $Q_t'(N_t) > 0$ and total chain sales, p_tQ_t are given by number of chain outlets, N_t, multiplied by sales per outlet, p_tq_t.

product concept). However, we cannot control for unobserved (to us) time-varying changes in chain characteristics (e.g. managerial changes over time) that could potentially bias our estimates. We expect this issue to be of less concern in our context, mostly due to the fact that the usual length of franchise contracts is between 10 and 20 years, and the average time period over which we observe a chain in our sample is relatively short, at about 5.3 years. Hence it is unlikely that unobserved managerial changes at the chain level, which are fairly infrequent events (MacIntosh and Palmer, 2008) would occur often enough to drive our results. We explore this issue further, however, by focusing on those chains that have at least 3 consecutive observations in our sample. We do this because low-performing chains should only make it sporadically into the rankings. If the negative scope effect above was due to the presence of relatively low-performing chains in our data, these subsample results should show no such effect. At the same time, the positive scale effects should be even stronger than before, because now we are left only with better managed and thus better performing chain/years. The second reason for this robustness check is more methodological - as Stock and Watson (2008) discuss, for panels with less than 3 observations per panel, the conventional heteroscedasticity-robust estimator of standard errors, unadjusted for clusters, is most efficient. Since we cluster standard errors at the chain level in all our estimations, it might be that for chains with less than 3 observations in our data, we actually overestimate standard errors in Tables 3 and 4. This could lead us to mistakenly conclude that effects are insignificant.

The results from this subsample in Tables 5 and 6, however, are very similar to our baseline results. In particular, scope still has a negative impact on the average number of outlets, and the scale coefficients in both tables are actually slightly lower than in the corresponding columns of Tables 3-4. Thus we conclude that neither low-performing chain/years in our data, nor the potential overestimation of standard errors for shorter panels, can explain our findings.

In the next set of columns in Tables 5 and 6, we examine more closely whether our main measure of parent company scope (based on all chains reported in the rankings), may suffer from measurement error due to changes in the number of chains reported each year in the listings. Thus, we replicate our regressions using our more conservative measure of scope – which relies only on the largest 200 chains each year. Not surprisingly, given Figure 1, and the fact that the two measures are very highly correlated (correlation coeff. = 0.98), we again obtain results that are very consistent with our baseline results (see columns 3 and 4, Tables 5 and 6).

4.3. Exploring Alternative Explanations

In this section, we explore additional explanations to further verify the robustness of our results and also better understand the channels behind our scale and scope effects.

We begin, in Table 7, by considering whether our scope measure might be omitting demand or reputation spillover effects, and whether this explains why we find no effect on outlet-level productivity and a negative impact of scope on number of outlets. In this table, we therefore use total sales of all other chains owned by the parent as our measure of scope. This alternative measure, however, does not have any effect on either sales per outlet or number of outlets, directly or through interactions with our parent change dummy variables. Moreover, the inclusion of this variable and its interaction with ownership changes does not affect the impact of scale nor the effect of our original measure of scope.[33] We conclude that the scope spillovers in our data again are best explained by the parent company's desire to rationalize their network of

[33] Since the sales of parent's other chains is a continuous variable with a very wide range of values (unlike our main scope measure based on number of chains) – see Table 1, we include it in logs and capture its impact on performance in the form of elasticity. Also, to avoid problems with taking the log of zero, we add 1 to the Sales of Parent's Other Chains before taking the log.

outlets and reduce competition among their branded offerings rather than by any cost efficiencies or positive demand spillover effects across different products/chains.

In Table 8, we exclude the few chains that experienced multiple parent changes during the period of our data. The subsample of chains that experienced just one parent change is interesting because the diversification literature suggests that managers may diversify into other activities for "managerial motives," namely to reduce their employment risk – e.g. by showing to shareholders that they are doing "something" – or to increase their personal compensation. Such scope changes would hurt the parent company since the target chains neither add value to the company nor increase its profitability, but rather fulfill managers' personal objectives. Alternatively, managers may underestimate the managerial or organizational cost of, and overestimate the benefits from, diversification and not realize that these costs may outweigh the benefits (see e.g. Shaver and Mezias, 2009). In either of these scenarios we would expect the chain to be resold to another parent soon after the first parent change occurs in our sample. Thus excluding the chains that changed parent multiple times within our data period allows us to explore whether our negative scope results may be driven by such "bad" diversification decisions. Table 8, however, shows that our results remain the same when we exclude these few chains. We conclude that managerial motives and inefficient diversification activities are not driving the negative effect of scope on number of outlets that we find in our data.

Finally, in Table 9, we explore how the extent of franchising in the target chains may affect the scale and scope effects. While our simple framework above assumed that chains are all franchised, the fact is that many chains in our data rely on company ownership for a good proportion of their outlets.[34] Since the extent of franchising does not vary much over time within chains (and thus is fundamentally captured by the chain fixed effects), we examine this issue by

[34] About 36% of the observations in our sample belong to chains that franchise 50% or less of their outlets.

exploring results for the subsample of chains in our data that franchise at least 80% of their outlets.[35] Our results again confirm all our previous findings, and further indicate that the negative scope effect on number of outlets is even stronger in this subsample of chains. This, in turn, implies that parents of franchised chains are especially interested in limiting inter-brand competition among the brands they manage.[36]

Through our empirical approach and the different specifications above we have tried as best we could to eliminate the possibility that some unobserved factors that could affect both our performance measures and our explanatory variables of interest may be biasing our results. Given the robustness of our results across specifications, and the similarity of estimated magnitudes throughout, we believe our results are not spurious. However, if there were some unobserved shocks that were not controlled for in our empirical approach, and that were not revealed either by our different specifications, and these shocks were serially correlated over time - as only then would our scale and scope variables measured at time *t-1* possibly be correlated with the idiosyncratic error at time *t* in our performance equation - then our estimates of scale and scope effects could be interpreted only as correlations and not as measures of causal effects. The usual remedy in this case would be to use an instrumental variable approach. Unfortunately, given our data and setting, we have no valid instrument for either scale or scope.

If we interpret our scale results as simple positive correlations, they still indicate that outlets belonging to chains that have grown larger in the previous year will have greater sales on average in the future. So a larger chain still represents an advantage for an outlet, chain and parent firm. Similarly, a negative correlation between parent company scope and number of

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[35] We use an 80% threshold because data on franchising suggest that this threshold identifies chains that are heavily invested in franchising (e.g. Blair and Lafontaine, 2005, p. 91 note that more than 70 percent of mature franchisors franchise 80% or more of their outlets).
[36] See the HBS case by Khanna and Ganot, on Choice Hotels International Inc., for a nice example of these issues.

outlets still suggests that the parent companies with greater scope have lower numbers of outlets on average per chain.

5. Conclusion

In this paper, we have analyzed the scale and scope externalities (or spillovers) that arise “within” franchised chains, and across franchised chains that are owned by the same parent company. Controlling for chain unobserved heterogeneity via fixed effects, we found robust evidence of positive scale effects within chains. Our findings further suggest that such positive scale spillovers operate through demand- rather than the cost- side of these chains. Given that franchising is used mostly in labor, and specifically low-skill labor, intensive industries such as retail and small-scale services, and given that we focus on large chains where the franchisor already should have developed an efficient business format (i.e. method of doing business) that should keep costs low, it is perhaps not surprising that the most important channel through which scale operates would be increased demand and reputation effects.

For parent company scope, we found no effect on the focal chain’s sales per outlet, and a negative rather than positive effect on its number of outlets. Moreover, chains that experience ownership changes see a reduction in their number of outlets in the year in which the change occurs and in future years as well. Since we find no effect on the chain’s sales per outlet, we conclude that the reduction in number of outlets is not a result of the new owner pruning poorly performing outlets. Instead, the lack of impact on sales per outlet, the reduction in number of outlets in the parent company chains after the change in ownership and the negative scope effect above all combine to imply that total chain sales go down in the long run when chains become part of more diversified parent companies.

Our negative scope effects moreover contradict the idea that increasing parent company scope yields important cost savings – the expected effect traditionally emphasized in the diversification literature – or that it yields major reputation/loyalty or entry deterrence benefits among multiple products “under the same roof.” Instead, our results are most consistent with the notion that exploiting some form of market-power is a primary reason why parent companies may benefit from owning more than one product concept.

We do not have price or parent company profit data to ascertain the effects of scale and scope on these variables directly. But the fact that our findings suggest that parent companies may be reducing quantity (i.e. the number of outlets), and thus exercising market power, is surprising on its own. In the type of industries where franchising occurs, one would expect that the ease of entry and relatively low switching costs between different products, compared to e.g. branded products in manufacturing such as cars, computers, etc., would seriously hamper the exercise of market power. Yet our findings are most consistent with parent companies taking steps to curb competition among their chains when they own more than one. We suspect that this occurs because the branding that is central to franchising differentiates product offerings in important ways, and this allows parent companies to benefit from keeping the number of outlets down.[37]

Of course, the branding and product differentiation that we see here also suggest that consumers value product variety in these industries. When increases in scope are organic (i.e. the parent company develops a new product/chain of its own rather than acquiring an existing chain), consumers may be willing to pay more and travel further for a given product in exchange for the resulting increased product variety. However, when increases in scope occur via chain acquisitions, the lower number of outlets of the acquired and other chains of the parent result in

[37] See also Sutton (1995) on endogenous barriers to entry, which include notably advertising and branding.

higher prices and higher travel costs for consumers, with no overall increase in product variety. Thus consumers are worse off when parent companies increase their scope by acquiring existing chains.

From a broader policy perspective, despite the very different setting of our analyses, our conclusions are quite consistent with Scherer's (2006) study where he found that the rise in mergers and acquisition activity in the U.S. has not had a positive effect on overall growth in U.S. productivity. In fact, our results suggest that even in industries where entry and exit costs are fairly low, firm decisions on scope, at least when their products tend to be substitutes, mostly seem to be driven by the desire to reduce the intensity of competition that they face.

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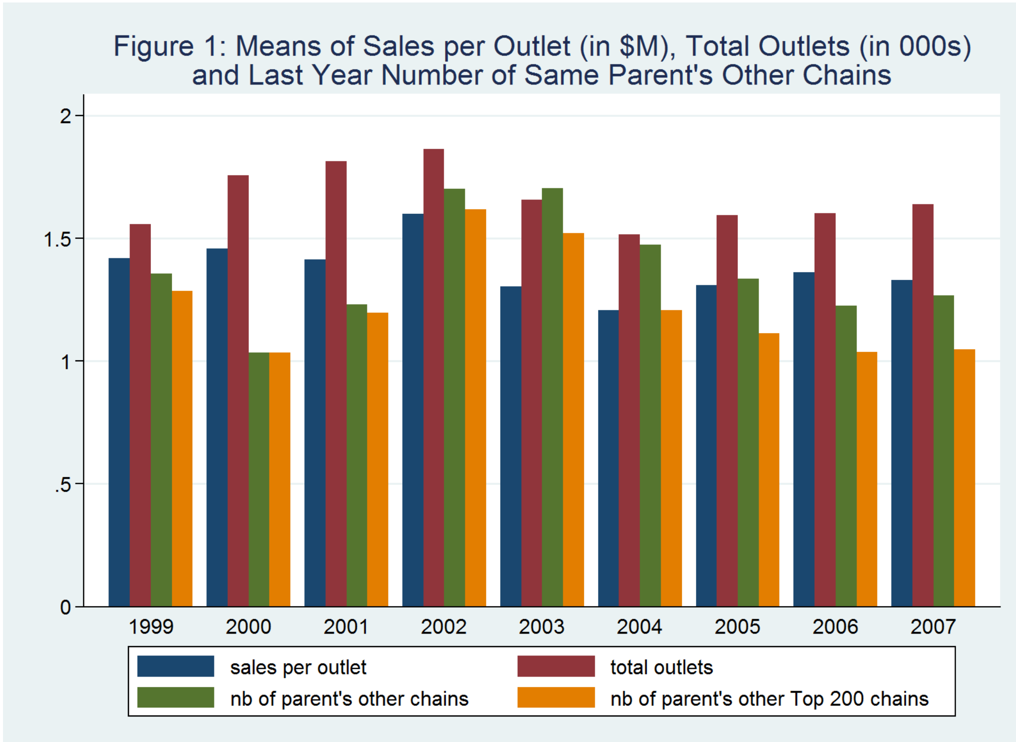
TABLE 1: DESCRIPTIVE STATISTICS, REGRESSION SAMPLES (SEE TABLES 3-4, COL. 1)

	Levels					Log				
	obs.	mean	sd	min	max	obs.	mean	sd	min	max
Sales per Outlet*	1970	1.54	2.33	0.021	28.9	1970	-0.12	1.02	-3.88	3.36
Total Outlets (Worldwide)	1972	1655.3	3633.6	29	33818	1972	6.42	1.26	3.37	10.4
Scale: Chain's Total Sales(t-1)	1972	1464.9	4103.5	38	56800	1972	6.24	1.30	3.64	10.9
Scope: # of Parent's Other Chains(t-1)	1972	1.37	2.48	0	12					
Alternative Scope Measures										
Scope: # of Parent's Other Top 200 Chains(t-1)	1972	1.22	2.24	0	11					
Scope: Sales of Parent's Other Chains(t-1)	1972	2342.7	5138.7	0	30800	1972	2.89	3.92	0	10.3
Parent Change Dummy Variables										
Short Run Effect:										
Parent Change Yr Dummy Var.	1961	0.037	0.19	0	1					
Long Run Effect:										
From Parent Change Yr Dummy Var.	1961	0.11	0.32	0	1					

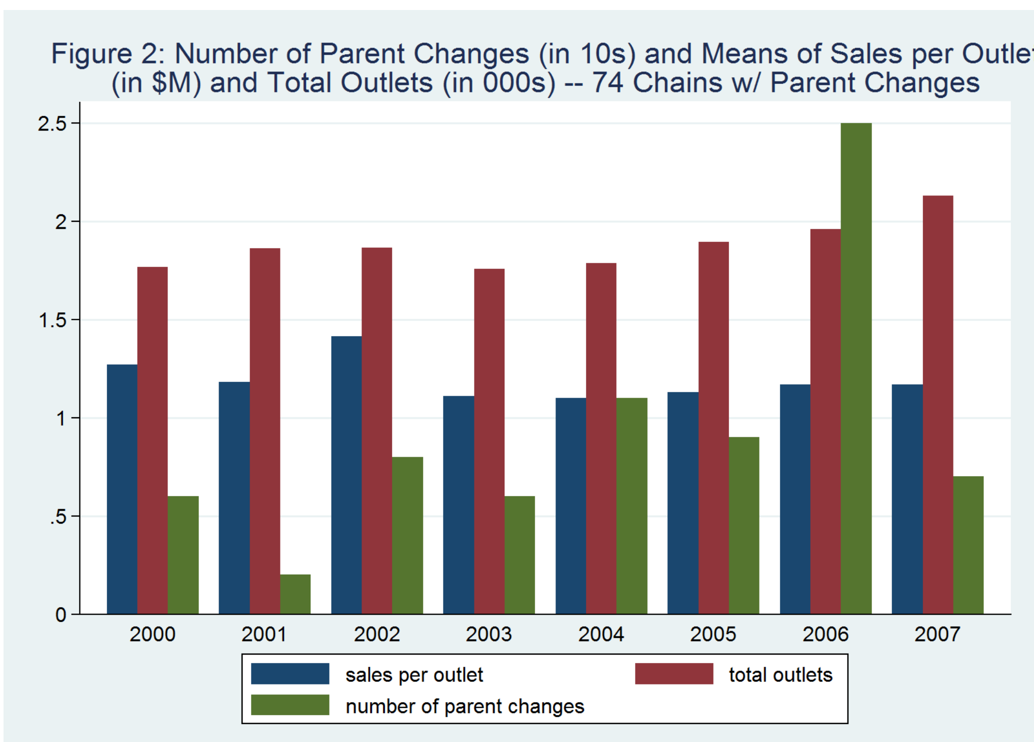
Notes: * All sales variables are in M of dollars; Scope = 0 if there are no other chains that could generate spillovers, i.e. chain does not have a parent that owns other chains. We add 1 to Sales of Parent's Other Chains before taking logs.

TABLE 2: DISTRIBUTION OF NO. OF CHAINS PER PARENT IN 1998 AND 2007.

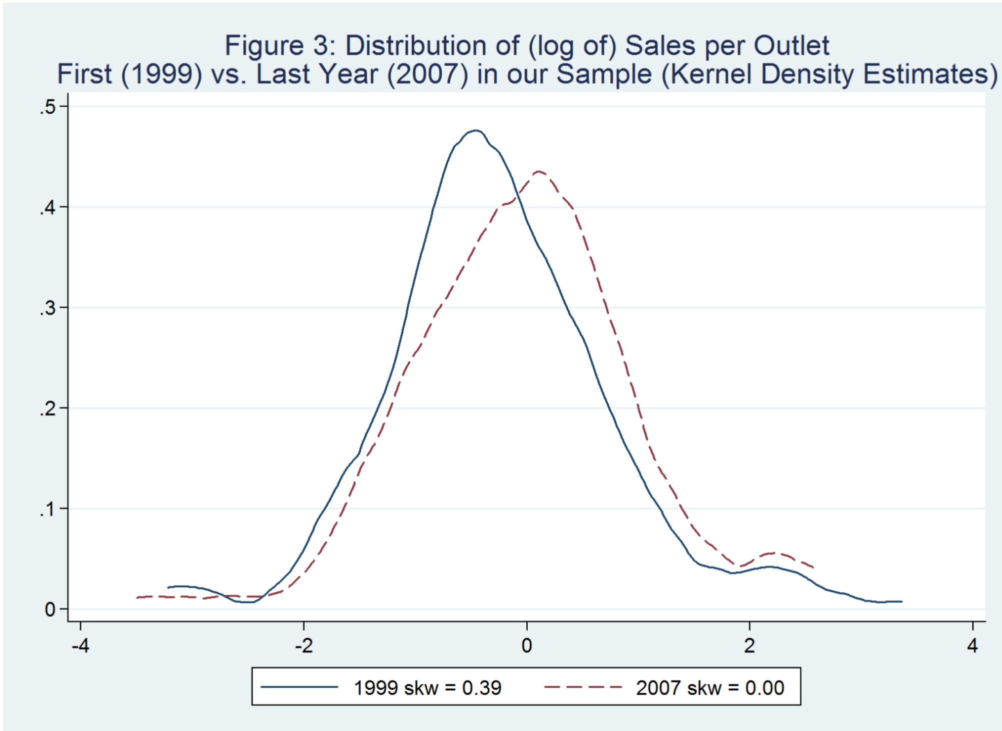
	Year: 1998		**Year: 2007**	
Number of chains per parent	# of chains owned by such parent	%	# of chains owned by such parent	%
1	138	61.33	199	66.33
2	22	9.78	26	8.67
3	24	10.67	18	6.00
4	12	5.33	8	2.67
5	5	2.22	15	5.00
6	6	2.67	18	6.00
7	7	3.11	7	2.33
9			9	3.00
11	11	4.89		
Total # of Chains	225		300	
Total # of Parents	164		228	



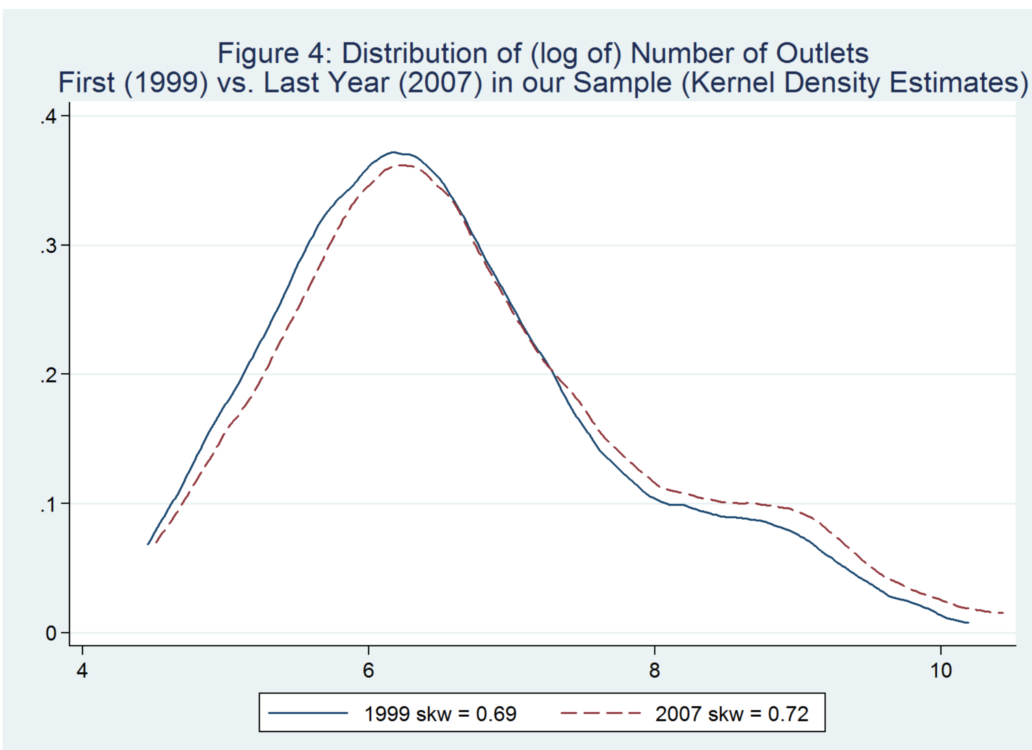
Note: Sales per outlet are deflated by the consumer price index to reflect inflation adjusted 1999 dollars.



Note: Sales per outlet are deflated by the consumer price index to reflect inflation adjusted 1999 dollars.



Note: Only the Top 200 chains are included in the graph in each of the two years. Sales per outlet are deflated by consumer price index to reflect inflation adjusted 1999 dollars.



Note: Only the Top 200 chains are included in the graph in each of the years.

TABLE 3: SALES PER OUTLET (LOGS). FIXED-EFFECTS ESTIMATION, 1999-2007

	(1)	(2)	(3)
Scale: Chain's Total Sales(t-1)	0.145***	0.144***	0.147***
	(0.035)	(0.035)	(0.036)
Scope: # of Parent's Other Chains(t-1)	0.008	0.008	0.007
	(0.009)	(0.009)	(0.009)
Parent Change Yr Dummy Var.		0.009	
		(0.028)	
Parent Change Yr Dummy Var. * Scope		-0.006	
		(0.005)	
From Parent Change Yr Dummy Var.			0.006
			(0.032)
From Parent Change Yr Dummy Var.*Scope			0.004
			(0.006)
Year dummy variables	Yes	Yes	Yes
Industry dummy variables * time trend	Yes	Yes	Yes
Observations	1970	1959	1959
Number of Chains	374	374	374
Adjusted R-squared	0.217	0.222	0.222

Notes: Variables in logs with the exception of dummy variables and # of Parent's Other Chains(t-1). We include the number of parent's other chains linearly, since most parent companies own no other chain (see text for more details). Significant at: *** 1%, ** 5%, * 10%. Standard errors corrected for heteroscedasticity and chain-level clusters in parentheses.

TABLE 4: TOTAL OUTLETS (LOGS). FIXED-EFFECTS ESTIMATION, 1999-2007

	(1)	(2)	(3)
Scale: Chain's Total Sales(t-1)	0.378***	0.377***	0.372***
	(0.040)	(0.041)	(0.041)
Scope: # of Parent's Other Chains(t-1)	-0.010**	-0.011**	-0.012**
	(0.005)	(0.005)	(0.005)
Parent Change Yr Dummy Var.		-0.057**	
		(0.027)	
Parent Change Yr Dummy Var. * Scope		0.002	
		(0.004)	
From Parent Change Yr Dummy Var.			-0.070**
			(0.031)
From Parent Change Yr Dummy Var.*Scope			0.002
			(0.006)
Year dummy variables	Yes	Yes	Yes
Industry dummy variables * time trend	Yes	Yes	Yes
Observations	1972	1961	1961
Number of Chains	374	374	374
Adjusted R-squared	0.430	0.436	0.439

Notes: Variables in logs with the exception of dummy variables and # of Parent's Other Chains(t-1). We include the number of parent's other chains linearly, since most parent companies own no other chain (see text for more details). Significant at: *** 1%, ** 5%, * 10%. Standard errors corrected for heteroscedasticity and chain-level clusters in parentheses.

TABLE 5: ROBUSTNESS CHECKS – SALES PER OUTLET (LOGS). FIXED-EFFECTS ESTIMATION, 1999-2007

	3 or more consecutive obs.		*Top 200 other chains*	
	(1)	(2)	(3)	(4)
Scale: Chain's Total Sales(t-1)	0.143***	0.146***	0.141***	0.145***
	(0.036)	(0.036)	(0.036)	(0.036)
Scope: # of Parent's Other Chains(t-1)	0.008	0.007	0.014	0.014
	(0.009)	(0.009)	(0.009)	(0.009)
Parent Change Yr Dummy Var.	0.009		0.010	
	(0.028)		(0.027)	
Parent Change Yr Dummy Var. * Scope	-0.006		-0.007	
	(0.005)		(0.006)	
From Parent Change Yr Dummy Var.		0.007		0.005
		(0.033)		(0.032)
From Parent Change Yr Dummy Var.*Scope		0.004		0.007
		(0.006)		(0.008)
Year dummy variables	Yes	Yes	Yes	Yes
Industry dummy variables * time trend	Yes	Yes	Yes	Yes
Observations	1909	1909	1959	1959
Number of Chains	326	326	374	374
Adjusted R-squared	0.221	0.222	0.224	0.224

Notes: Variables in logs with the exception of dummy variables and # of Parent's Other Chains(t-1). We include the number of parent's other chains linearly, since most parent companies own no other chain (see text for more details). Significant at: *** 1%, ** 5%, * 10%. Standard errors corrected for heteroscedasticity and chain-level clusters in parentheses.

TABLE 6: ROBUSTNESS CHECKS - CHAIN'S TOTAL OUTLETS (LOGS). FIXED-EFFECTS ESTIMATION, 1999-2007

	3 or more consecutive obs.		*Top 200 other chains*	
	(1)	(2)	(3)	(4)
Scale: Chain's Total Sales(t-1)	0.374***	0.370***	0.378***	0.373***
	(0.041)	(0.041)	(0.041)	(0.041)
Scope: # of Parent's Other Chains(t-1)	-0.011**	-0.012**	-0.011*	-0.013*
	(0.005)	(0.005)	(0.006)	(0.006)
Parent Change Yr Dummy Var.	-0.057**		-0.055**	
	(0.027)		(0.026)	
Parent Change Yr Dummy Var. * Scope	0.002		0.001	
	(0.004)		(0.005)	
From Parent Change Yr Dummy Var.		-0.067**		-0.067**
		(0.031)		(0.031)
From Parent Change Yr Dummy Var.*Scope		0.002		0.001
		(0.006)		(0.007)
Year dummy variables	Yes	Yes	Yes	Yes
Industry dummy variables * time trend	Yes	Yes	Yes	Yes
Observations	1910	1910	1961	1961
Number of Chains	326	326	374	374
Adjusted R-squared	0.434	0.437	0.435	0.439

Notes: Variables in logs with the exception of dummy variables and # of Parent's Other Chains(t-1). We include the number of parent's other chains linearly, since most parent companies own no other chain (see text for more details). Significant at: *** 1%, ** 5%, * 10%. Standard errors corrected for heteroscedasticity and chain-level clusters in parentheses.

TABLE 7: ARE WE OMITTING DEMAND/REPUTATION SPILLOVERS? FIXED-EFFECTS ESTIMATION, 1999-2007

Dependent Variable(in logs):	*Sales Per Outlet*		*Total Outlets*	
	(1)	(2)	(3)	(4)
Scale: Chain's Total Sales(t-1)	0.143***	0.146***	0.378***	0.373***
	(0.035)	(0.035)	(0.040)	(0.040)
Scope: # of Parent's Other Chains(t-1)	0.010	0.011	-0.014**	-0.016***
	(0.013)	(0.013)	(0.006)	(0.006)
Alt. Scope: Sales of Parent's Other Chains(t-1)	-0.003	-0.005	0.004	0.006
	(0.007)	(0.008)	(0.005)	(0.005)
Parent Change Yr Dummy Var.	-0.0003		-0.036	
	(0.028)		(0.027)	
Parent Change Yr Dummy Var. * Scope	-0.012		0.016	
	(0.013)		(0.012)	
Parent Change Yr Dummy Var. *Alt. Scope	0.006		-0.014	
	(0.012)		(0.012)	
From Parent Change Yr Dummy Var.		-0.011		-0.049
		(0.034)		(0.033)
From Parent Change Yr Dummy Var. * Scope		-0.007		0.015
		(0.009)		(0.010)
From Parent Change Yr Dummy Var. * Alt. Scope		0.011		-0.013
		(0.009)		(0.010)
Year dummy variables	Yes	Yes	Yes	Yes
Industry dummy variables * time trend	Yes	Yes	Yes	Yes
Observations	1959	1959	1961	1961
Number of Chains	374	374	374	374
Adjusted R-squared	0.222	0.223	0.437	0.441

Notes: Variables in logs with the exception of dummy variables and # of Parent's Other Chains(t-1). We include the number of parent's other chains linearly, since most parent companies own no other chain (see text for more details). Significant at: *** 1%, ** 5%, * 10%. Standard errors corrected for heteroscedasticity and chain-level clusters in parentheses.

TABLE 8: EXCLUDING CHAINS WITH MULTIPLE OWNERSHIP CHANGES. FIXED EFFECT ESTIMATION, 1999-2007

Dependent Variable (in logs):	*Sales Per Outlet*		*Total Outlets*	
	(1)	(2)	(3)	(4)
Scale: Chain's Total Sales(t-1)	0.143***	0.146***	0.379***	0.374***
	(0.036)	(0.036)	(0.041)	(0.041)
Scope: # of Parent's Other Chains(t-1)	0.008	0.007	-0.011**	-0.012**
	(0.009)	(0.009)	(0.005)	(0.005)
Parent Change Yr Dummy Var.	0.005		-0.060**	
	(0.030)		(0.030)	
Parent Change Yr Dummy Var. * Scope	-0.005		0.003	
	(0.005)		(0.004)	
From Parent Change Yr Dummy Var.		0.008		-0.073**
		(0.035)		(0.034)
From Parent Change Yr Dummy Var.*Scope		0.004		0.002
		(0.006)		(0.006)
Year dummy variables	Yes	Yes	Yes	Yes
Industry dummy variables * time trend	Yes	Yes	Yes	Yes
Observations	1930	1930	1932	1932
Number of Chains	369	369	369	369
Adjusted R-squared	0.223	0.224	0.437	0.441

Notes: Variables in logs with the exception of dummy variables and # of Parent's Other Chains(t-1). We include the number of parent's other chains linearly, since most parent companies own no other chain (see text for more details). Significant at: *** 1%, ** 5%, * 10%. Standard errors corrected for heteroscedasticity and chain-level clusters in parentheses.

TABLE 9: CHAINS THAT FRANCHISE MORE THAN 80% OF OUTLETS. FIXED EFFECT ESTIMATION, 1999-2007

Dependent Variable (in logs):	*Sales Per Outlet*		*Total Outlets*	
	(1)	(2)	(3)	(4)
Scale: Chain's Total Sales(t-1)	0.163***	0.170***	0.340***	0.330***
	(0.046)	(0.045)	(0.048)	(0.046)
Scope: # of Parent's Other Chains(t-1)	0.010	0.010	-0.015**	-0.018***
	(0.012)	(0.012)	(0.006)	(0.006)
Parent Change Yr Dummy Var.	0.013		-0.056**	
	(0.041)		(0.025)	
Parent Change Yr Dummy Var. * Scope	-0.006		0.003	
	(0.006)		(0.004)	
From Parent Change Yr Dummy Var.		0.022		-0.113***
		(0.049)		(0.039)
From Parent Change Yr Dummy Var.*Scope		0.005		0.002
		(0.007)		(0.006)
Year dummy variables	Yes	Yes	Yes	Yes
Industry dummy variables * time trend	Yes	Yes	Yes	Yes
Observations	1286	1286	1287	1287
Number of Chains	249	249	249	249
Adjusted R-squared	0.236	0.238	0.420	0.436

Notes: Variables in logs with the exception of dummy variables and # of Parent's Other Chains(t-1). We include the number of parent's other chains linearly, since most parent companies own no other chain (see text for more details). Significant at: *** 1%, ** 5%, * 10%. Standard errors corrected for heteroscedasticity and chain-level clusters in parentheses.

APPENDIX

Industry Group	Number of Obs.	%	Number of Chains	%
Automotive Products & Services	113	5.7	21	5.6
Business Services	80	4.1	17	4.5
Business Supplies	24	1.2	4	1.1
Contractors	37	1.9	10	2.7
Cosmetic Products & Services	47	2.4	7	1.9
Eating Places - Full Service	262	13.3	46	12.3
Eating Places - Limited Services	515	26.1	93	24.9
Education	19	1.0	4	1.1
Health & Fitness Products & Svcs	50	2.5	12	3.2
Hotels & Motels	362	18.4	51	13.6
Maintenance	78	4.0	17	4.5
Personal Services	61	3.1	15	4.0
Real Estate	33	1.7	8	2.1
Recreation and Travel	31	1.6	7	1.9
Rental	52	2.6	11	2.9
Retail - Building Materials	19	1.0	3	0.8
Retail - Food	35	1.8	9	2.4
Retail - Home Furnishings	13	0.7	7	1.9
Retail - Other	123	6.2	29	7.8
Retail - Used Products	18	0.9	3	0.8